IJITCE

ISSN 2347- 3657

International Journal of
Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp715-725

DEEPDIABETIC: DEEP NEURAL NETWORK APPROACH FOR EARLY DIAGNOSIS OF DIABETIC EYE DISEASES

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ABSTRACT

Medical imaging diagnosis, image detection, and image classification are all successfully and significantly impacted by deep learning (DL). Diabetic eye disease will be the primary cause of vision loss worldwide, and diabetes is a serious public health problem. The DeepDiabetic framework is a multi-classification deep learning model that was presented in this study to diagnose and classify four distinct diabetic eye diseases: cataract, glaucoma, diabetic macular oedema, and diabetic retinopathy (DR). 1228 photos from six distinct datasets (DIARETDB0, DIARETDB1, Messidor, HEI-MED, Ocular, and Retina) were used to evaluate the suggested models. We evaluated the deep learning models' performance using two distinct geometric augmentation techniques, known as online augmented and offline augmented, in addition to the original dataset. EfficientNetB0, VGG16, ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), and ResNet152V2 + Bidirectional GRU (Bi-GRU) are the five architectures whose performances are examined in this study. These deep learning architectures are thoroughly analysed and evaluated utilising four classes of public fundus datasets (DR, DME, Glaucoma, and Cataract). To the best of our knowledge, the literature does not include any more deep learning models for selecting amongst these models for these particular disorders. The EfficientNetB0 model performs better than the other four suggested models, according on the experiment findings. Based on fundus pictures, the EfficientNetB0 model obtained accuracy, recall, precision, and AUC of 0.9876, 0.9876, and 0.9977, respectively. While the accuracy of the other research was only 88.33%, 89.54%, 97.23%, and 80.33%, respectively, our EfficientNetB0 model reaches 98.76%. Our EfficientNetB0 model delivers much greater accuracy, recall, precision, and AUC when compared to other research such as Fast-RCNN, RCNN-LSTM, and InceptionResNet. The results show that our suggested models—particularly the EfficientNetB0 model—are noticeably more accurate than the most advanced models.

I. INTRODUCTION

Deep learning (DL) is showing very high performance in categorisation tests and is being applied in various sectors to find novel solutions to pressing problems. Tools and methods from artificial intelligence (AI) are suitable for use in medicine. One of the 21st century's most potently revolutionary technologies is artificial intelligence. Deep convolutional networks, generative adversarial networks (GANs), deep reinforcement learning (DRL), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and artificial neural networks (ANNs) are some of the potent machine learning (ML) tools and techniques that were used to bring about this change. Deep learning (DL) has recently surpassed conventional artificial intelligence (AI) in important tasks including natural language creation, picture characterisation, and voice recognition.

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In several areas of medical imaging diagnostics, including image detection and classification, DL has been shown to be an effective and significant technique. By using fundus pictures to analyse and diagnose eye disorders, DL may be used to identify and categorise eye conditions, including diabetic eye disease. Diabetic eye illness include diabetic retinopathy (DR), diabetic macular oedema (DME), cataracts, and glaucoma. Diabetic eye disease may cause significant vision loss or even reduced eyesight in patients between the ages of 20 and 74. If diabetic eye disease is not detected early, vision loss cannot be prevented. If diabetic eye damage is identified, 90% of diabetics can prevent it [1].

Improving DL detection models for diabetic eye disorders is the goal of this study. It is necessary to get fundus photos of diabetic eye illness in order to feed them into DL models. A number of image preparation methods are then applied to the pictures. Using pre-processed photos, features are automatically extracted and analysis rules are learnt. The authors of [2] examined the interest in using machine learning (ML) for respiratory illness detection and classification, encompassing the most important papers released from 2018 until the end of 2021. These results might help the researchers better organise their work and make more valuable contributions to the area. Therefore, we discovered that Ibrahim et al. [3] used TL on a set of CT scan and chest X-ray images for multiclass classification utilising the ResNet152V2 + gated recurrent unit (GRU), ResNet152 V2 + bidirectional GRU (Bi-GRU), and VGG19-CNN architectures. Since GRU and Bi-GRU are models that have never been employed in this sector, their research's advancements were very rich and inspired us to use them in the multiclassification of diabetic eye illnesses. Additionally, Eko et al. [4] found that improving the classification accuracy of diabetic eye disorders may be achieved by combining EfficientNetB7 models with certain augmentation procedures.

Models like VGG16, EfficientNetB0, and ResNet152V2 are selected as CNN pre-trained models in this study. Furthermore, ResNet152V2 is even integrated with the GRU and Bi-GRU RNN models. Owing to dataset availability constraints, we used two distinct geometric augmentation techniques in addition to the original dataset to assess the deep learning models' performance. These techniques are known as offline enhanced geometric augmentation and online augmented geometric augmentation.

One of the most common illness categories in the world today is diabetes. Visual loss may result from diabetic fundus disorders, which are the primary cause of blindness. Visual function is currently impacted by fundus disorders, glaucoma, cataracts, and DR [2]. Fundus disease cannot be precisely addressed until it has progressed to the point where it significantly compromises the patient's vision. It is challenging to accurately diagnose diabetic retinopathy using retinal fundus pictures since even highly qualified eye experts often misidentify eye abnormalities. Since early illness diagnosis prevents blindness, it is advantageous to support a method that aids in disease detection.

CNN has had remarkable success with fundus photos because of its strong feature-learning capabilities. Numerous deep learning architectures have been reported in the literature, and they have shown exceptional performance in identifying specific diabetic eye conditions. To the best of our knowledge, the categorisation model of the four diabetic diseases—DR, DME, glaucoma, and cataract—had hardly been addressed at the start of our study. However, we discovered that Rubina Sarki et al. [5] had recently proposed a categorisation scheme for

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those four disorders by the end of 2021. However, their dataset revealed class imbalance, and they only used one CNN model in their study. Compared to previous studies in DL classifications, their accuracy of 81.33% is still regarded as inadequate.

According to earlier research, there were insufficient investigations examining the categorisation and prediction of cataract illness [6]. In order to categorise cataract illness independently, these investigations were also conducted independently. Since DME illness identification is extremely likely to indicate that the retina is developing DR, Reference [7] suggested DME disease detection as the research gap. This helps researchers better understand the origins of retina-based disorders. Training limited data and datasets with a class imbalance between various illnesses are the focus of the future DL model. If the training set is too small, the results' accuracy may degrade. The use of enhancement techniques via conventional data augmentation is considered a suitable option.

This study's primary contributions are:

• Present the DeepDiabetic Framework, a multiclass deep learning model for identifying and diagnosing the four most prevalent diabetic eye complications: cataract, glaucoma, diabetic macular oedema, and diabetic retinopathy (DR).

• In addition to the original dataset, we used both offline and online geometric augmentation techniques to evaluate the deep learning models' correctness.

• This article considers the performance of five different architectures: ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), ResNet152V2 + Bidirectional GRU (Bi-GRU), EfficientNetB0, and VGG16. a detailed analysis and assessment of various deep learning architectures (DR, DME, Glaucoma, and Cataract) using public fundus datasets with four classes. To the best of our knowledge, no other GRU models have been employed in the literature to categorise these models for these specific disorders.

• Comparing our proposed work's performance metrics with several models used in previous research to diagnose and categorise diabetic eye diseases.

A summary of the literature review is given in Section II, the study's dataset is described in Section III, and the experimental setup used to develop the framework—including the deep learning suggested classification models—is explained in Image Augmentation. While the comparative analysis and debate are shown in Section V, the findings and comments are presented in Section IV. Lastly, the work is concluded in Section VI.

II. LITERATURE SURVEY

An overview of the role of early screening for diabetic retinopathy in individuals with diabetes mellitus was published by P. Vashist, N. Gupta, S. Singh, and R. Saxena. Indian Journal of Community Medicine, vol. 36, no. 4, 2011, p. 247.

In India, diabetes has become a serious public health issue. In India, an estimated 40 million people had diabetes in 2007, and by 2025, that figure is expected to increase to about 70 million. The incidence of diabetes and its related consequences, including neuropathy, nephropathy, vascular disorders (cardiac, cerebral, and peripheral), and retinopathy, is on the rise due to the effects of rapid urbanisation, industrialisation, and lifestyle changes. In India, diabetic retinopathy is a major contributor to preventable blindness. The burden of blindness from diabetic retinopathy may be decreased by treatment efforts in the early stages of the condition. Given the affordable early screening techniques now accessible, suitable models and strategies must be created. At every level of the hierarchy, from basic health centres to specialised eye care facilities, such models must include a well-developed mechanism for

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screening, diagnosis, and referral. To detect diabetic retinopathy, the Indian National Program for Control of Blindness advises opportunistic screening. For the purposes of screening, diagnosis, and referral, any chance to come into touch with high-risk instances of diabetes and/or diabetic retinopathy should be taken advantage of. Every stakeholder, including the commercial sector, must contribute. The whole concept should also include behaviour modification and awareness-raising among diabetes and care support systems. In order to reach a bigger population and increase compliance for ongoing treatment, community involvement and changing diabetics' health-seeking behaviour may play a significant role.

"Trends of using machine learning for detection and classification of respiratory diseases: InvestigationNand analysis," by B. Aljaddouh and D. Malathi Mater. Today, Proc., January 2022, vol. 62, pp. 4651–4658.

Numerous researchers from a variety of professions are tasked with addressing the development of respiratory infections because of their simple dissemination, which greatly increases the danger of these illnesses. Covid-19 is the most well-known of these illnesses and a more recent problem. In this study, a thorough assessment of previous research on machine learning-based respiratory illness detection and classification was carried out. The fifty most significant publications published between 2018 and the end of 2021 are included in the study. The study's findings provide an examination of current research patterns in this area with regard to the methods and information used. Before beginning this area of study, these findings help prospective researchers make an informed decision on how best to design their work.

"Deep-chest: Multiclassification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases," by D. M. Ibrahim, N. M. Elshennawy, and A. M. Sarhan Art. no. 104348 in Comput. Biol. Med., vol. 132, May 2021.

Globally, Corona Virus Disease (COVID-19) is quickly spreading and has been declared a pandemic. Many affected individuals may be protected if COVID-19 is detected early. Sadly, COVID-19 may be misdiagnosed as lung cancer or pneumonia, which can quickly spread to the chest cells and kill a patient. Chest X-rays and computed tomography (CT) scans are the most widely utilised diagnostic techniques for these three conditions. This study proposes a multi-classification deep learning model for combining chest x-ray and CT images to diagnose lung cancer, pneumonia, and COVID-19. A CT scan of the chest is helpful even before symptoms develop, and CT can accurately identify the aberrant characteristics that are recognised in pictures. This combination has been employed since chest X-rays are less effective in the early stages of the illness. Additionally, the dataset size will grow with the use of these two picture formats, improving the classification accuracy. As far as we are aware, there isn't any deep learning model in the literature that can distinguish between these illnesses. Four architectures—VGG19-CNN, ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), and ResNet152V2 + Bidirectional GRU (Bi-GRU)—are examined in this study for their performance. Public digital chest x-ray and CT datasets with four classifications (normal, COVID-19, pneumonia, and lung cancer) are used to offer a thorough assessment of several deep learning architectures. The VGG19 + CNN model performs better than the three other suggested models, according to the experiment findings. Based on X-ray and CT images, the VGG19+CNN model obtained 98.05% accuracy (ACC), 98.05% recall, 98.43% precision, 99.5% specificity (SPC), 99.3% negative predictive value (NPV), 98.24% F1 score, 97.7%

Matthew's correlation coefficient (MCC), and 99.66% amount of area under the curve (AUC).

Y. Azhar, F. Bimantoro, H. A. Nugroho, Z. Ibrahim, A. E. Minarno, and M. H. C. Mandiri, "Diabetic retinopathy disease classification using convolutional neural network," Journal of Information Visualisation, Volume 6, Issue 1, Pages 12–18, 2022

Diabetic Retinopathy (DR) is a condition that makes people blind or visually impaired. A condition of swelling and leaking in the blood vessels at the rear of the retina of the eye is the hallmark of diabetic retinopathy illness. An skilled ophthalmologist is necessary for early diagnosis using the retinal fundus picture of the eye, which may take some time. This research suggested using the Efficientnet-b7 model, a deep learning technique, to automatically detect diabetic retinopathy. Three preprocessing methods that might be used with the "APTOS 2019 Blindness Detection" dataset are used in this research. With an accuracy of 89% of train data and 84% of test data, the Usuyama preprocessing technique outperformed the Harikrishnan preprocessing technique, which had 82% accuracy in test data, and the Ben Graham preprocessing technique, which had 81% accuracy in test data, in the preprocessing technique trial scenarios. Hyperparameter tweaking was used in this work to determine the optimal settings to apply to the EfficientNet-B7 Model. In contrast to models without augmentation, we evaluated the Efficientnet-B7 model in this work using an augmentation procedure that may lessen the incidence of overfitting. Techniques for preprocessing and augmentation may affect the performance outcomes of the suggested EfficientNet-B7 model and lessen model overfitting.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM

In diabetic eye illness, the Transfer Learning (TL) technique is often used, as shown by the authors in [29], [30], [31], [32], [33], and [34]. The TL initialises parameters using knowledge from previous learning rather than creating them at random. Core characteristics like edges, textures, etc. are intuitively extracted by the first layers. Like blood vessels and exudates, the upper layers are more specific to the job at hand. TL is successfully used in [29], [32], [33], and [34] when there is not enough data to train a neural network from scratch. Pan and associates [29] examined four different DR lesion types and compared three CNN models: DenseNet, ResNet50, and VGG16. The results of the experiment demonstrate that DenseNet is an efficient model for automatically recognising and differentiating retinal lesions in multi-label categorised pictures. However, since microaneurysms are readily misclassified in the ubiquitous presence of fluorescein, the technique does not reliably identify them.

Additionally, using a small dataset, Samanta et al. [30] developed a CNN-based TL architecture based on colour fundus photography that performs rather well in identifying DR (No DR, Mild DR, Moderate DR, and Proliferative DR) from hard exudates, blood vessels, and texture. They applied their model to a number of frameworks, such as ResNet-50, DenseNet, AlexNet, Xception, VGG16, Inceptionv1, Inceptionv2, and Inceptionv3. A framework for actively identifying the presence and severity of DR was given by Zhang et al. [31]. via the use of many TL designs, including InceptionResNetV2, DenseNets, Xception, ResNet50, and InceptionV3. Even though the suggested framework achieved a 97.5% sensitivity and a 97.7% specificity, a larger and more comprehensive dataset is required to evaluate their model. In order to improve accuracy and save processing time, the CNN model and Lookahead optimiser were also used in [32] for the image categorisation of cataract illness. The model was able to correctly identify the pictures' label by using the CNN-AlexNet architecture, the Lookahead optimiser on stochastic gradient descent, and Adam. CNN-AlexNet thus improves optimiser stochastic gradient descent by 2.5 percent and raises accuracy by 20 percent. In order to support the early diagnosis of diabetic eye disorders (DR, DME, and glaucoma), Sarki et al. [34] presented a deep learning architecture that combined image processing approaches with 13 CNN models.

Several problems were identified with the early categorisation of diabetic eye illness. They subsequently developed an automated classification system that looked at moderate multi-class diabetic eye illness as well as multi-class [33]. The VGG16 and InceptionV3 were used to apply various performance enhancement strategies, such as fine-tuning, optimising, and contrast increasing. Furthermore, the VGG16 model achieved moderate multi-class classification accuracy of 85.95% and multi-class classification accuracy of 88.3%.

Disadvantages

- Data complexity: In order to identify diabetic eye diseases, the majority of machine learning models now in use must be able to correctly comprehend sizable and intricate datasets.
- Data availability: In order to provide precise predictions, the majority of machine learning models need a lot of data. The accuracy of the model may degrade if data is not accessible in large enough amounts.
- Inaccurate labelling: The accuracy of the machine learning models now in use depends on how well the input dataset was used for training. Inaccurate labelling of the data prevents the model from producing reliable predictions.

PROPOSED SYSTEM

- Present the DeepDiabetic Framework, a multiclassification deep learning model designed to identify and diagnose the four most prevalent diabetic eye complications: cataract, glaucoma, diabetic macular oedema, and diabetic retinopathy (DR).
- In addition to the original dataset, we used both offline and online geometric augmentation techniques to evaluate the deep learning models' correctness.
- This article considers the performance of five different architectures: ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), ResNet152V2 + Bidirectional GRU (Bi-GRU), EfficientNetB0, and VGG16. a detailed analysis and assessment of various deep learning architectures (DR, DME, Glaucoma, and Cataract) using public fundus datasets with four classes. To the best of our knowledge, no other GRU models have been used in the literature to categorise these models for these specific disorders.
- Evaluating our proposed work's performance metrics against other models used in earlier research to diagnose and categorise diabetic eye diseases.

ADVANTAGES

- Method 1: Dataset without augmentation This approach makes use of the original, unaltered dataset of 1228 photos that was gathered and stated in Data Collection III-A1.
- Technique 2: Augmented dataset online With this approach, the augmentation is applied as the model is being trained. This implies that the model is given a batch of the original dataset chosen at random for each epoch, and the changes are then carried out live. Furthermore, depending on the transformations used, the pictures supplied to the model vary for every epoch.

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
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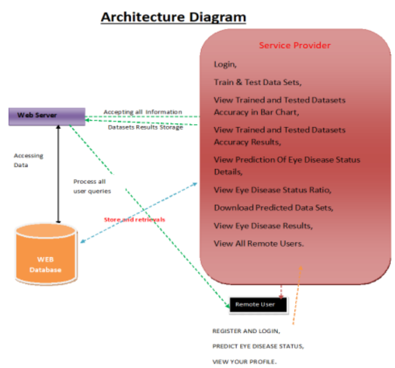
- Method 3: Dataset that has been enhanced offline Prior to being used in the model, this technique adds the augmentation to the original dataset. As previously mentioned, the initial dataset is divided into two sets at random: the training set and the validation set. In this case, we merely amplify the training set of photographs, which consists of around 858 photos. We created a total of 6006 pictures by applying six distinct alterations to each image (in addition to the original image).

SYSTEM ARCHITECTURE



IV. IMPLEMENTATION

Modules Description

Service Provider

The Service Provider must use a working user name and password to log in to this module. He may do many tasks after successfully logging in, including Train & Test Data Sets, See the Accuracy of Trained and Tested Datasets in a Bar Chart View Accuracy Results for Trained and Tested Datasets, Download Predicted Data Sets, View Eye Disease Status Ratio, and View Prediction Details View All Remote Users and View Eye Disease Results.

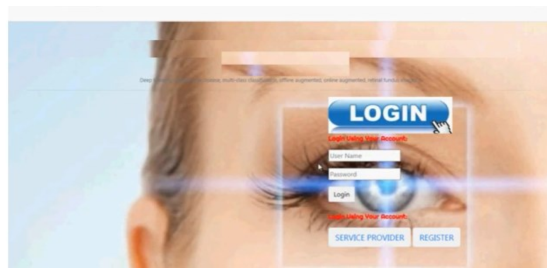
View and Authorize Users

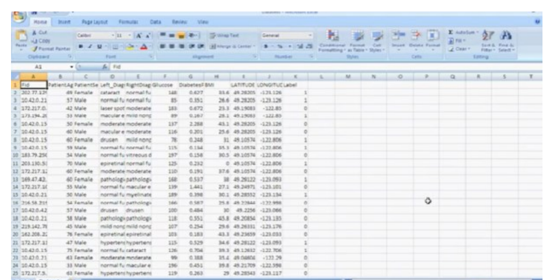
The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

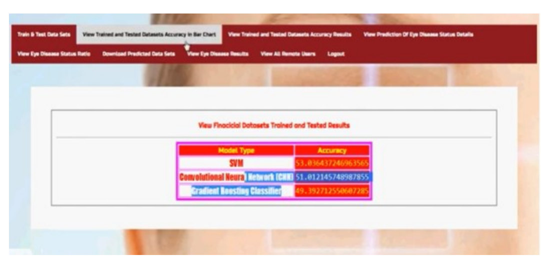
Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. Following a successful login, the user may do tasks including registering and logging in, predicting their eye disease status, and seeing their profile.

V. SCREEN SHOTS







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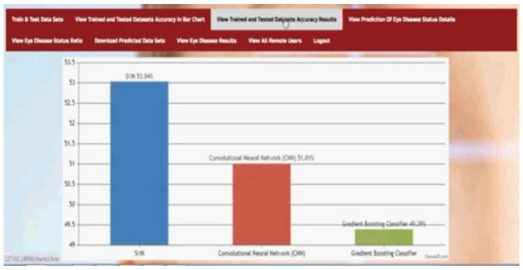

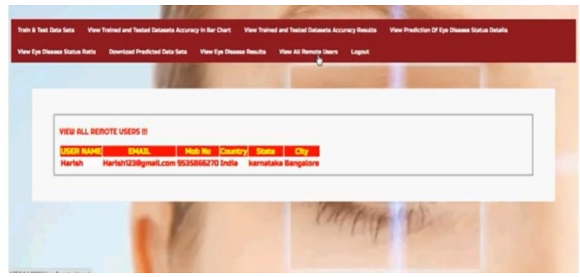

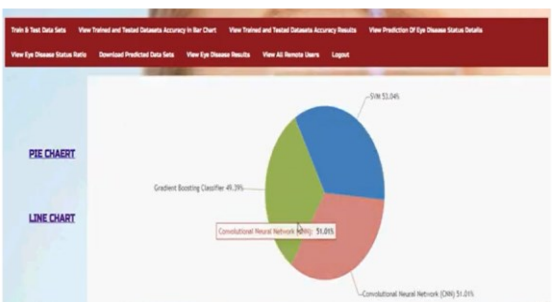

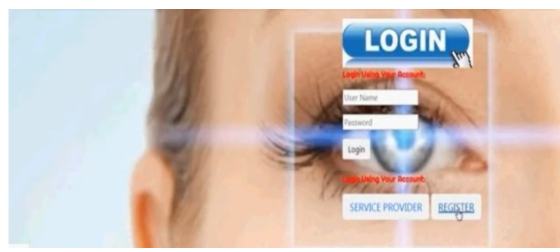

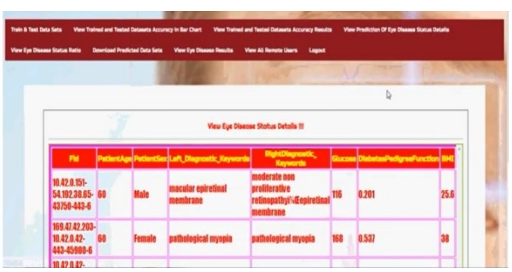

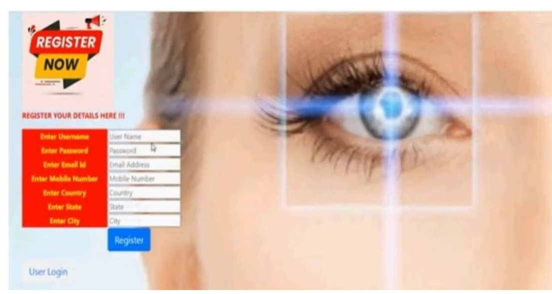

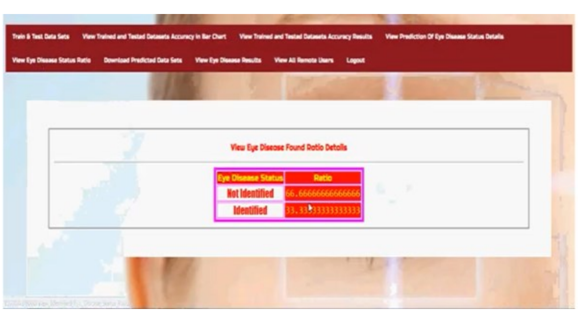

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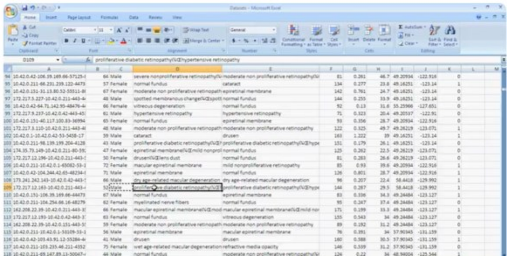

VI. CONCLUSION

The Deep Diabetic framework, a multi-classification deep learning model, was created and assessed in this study to identify DR, DME, glaucoma, and cataract from fundus photos. To choose the best course of therapy, it's critical to accurately identify these illnesses as soon as possible. Even highly skilled ophthalmologists are prone to misdiagnosing eye lesions, and fundus pictures make correct identification difficult.

As far as we are aware, no additional GRU models that choose amongst DR, DME, cataract, and glaucoma are available in the literature. This study included five model architectures: ResNet152V2, GRU+ResNet152V2, Bi-GRU+ResNet152V2, VGG16, and EfficientNetB0. Despite this study, the main goal was to give a multi-classification of the four diabetic eye illnesses, which poses a significant challenge. The majority of earlier studies concentrated on the classification and development of a single fundus disease independently. To investigate the method's resilience and flexibility in handling real-world situations, this study combined datasets from many sources.

This article tested the suggested models' accuracy, precision, f1-score, recall, and AUC. While Vgg16 [33], RCNN-LSTM [12], Vgg16 [13], and CNN [5] only attain 88.33%, 89.54%, 97.23%, and 80.33% accuracy, respectively, our EfficientNetB0 model obtains 98.76% accuracy. Comparing our EfficientNetB0 model to Fast-RCNN [27], RCNNLSTM [12], and InceptionResNet [18], we find that the AUC of 99.77% is much higher. In contrast to Vgg16 [33], Fast-RCNN [27], RCNN-LSTM [12], Vgg16 [13], ResNet34 [13], MobileNetV2 [13], and Efficient Net [13], which have accuracy rates of 88.3%, 95.2%, 89.54%, 97.23%, 90.85%, 94.32%, and 93.82%, respectively, our EfficientNetB0 model achieves 98.76%. Our EfficientNetB0, Vgg16, ResNet152V2, GRU+ResNet152V2, and Bi-GRU+ResNet152V2 models have, as you can see, respective AUCs of 99.77%, 99.47%, 99.6%, 99.8%, and 99.8%. It was 95.64% for Fast-RCNN [27], 96.8% for RCNN-LSTM [12], and 96.8% for InceptionResNet [18]. In a similar vein, the table displays the variations in accuracy, f1-score, and recall assessment measures between our study and the earlier research. The results show that our proposed Efficient-NetB0 model outperforms the state-of-the-art models in terms of accuracy.

Our five multi-classification models of the four diabetes illnesses (DR, DME, glaucoma, and cataract) produced the greatest accuracy result in the state-of-the-art, as far as we are aware. Based on fundus pictures, the EfficientNetB0 model obtained 98.76% accuracy, 98.76% recall, 98.76% precision, and 99.73% AUC. In a comprehensive series of

ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp715-725

trials and findings employing fundus pictures from various sources, the EfficientNetB0 model outperformed the other five suggested models.

To improve the clinical acceptability of deep learning models, future research should focus on comprehending different aspects of deep neural networks and visualisation. In the future, we will need to gather massive training datasets from other hospitals employing other kinds of cameras, including tens of thousands of anomalous instances. Therefore, more characteristics will be included to improve generalisation and accuracy.

More pictures in the datasets utilised, training epochs, and the usage of other GAN architectures and other deep learning methods for classification and improvement might all improve the performance of the proposed model.

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International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

https://doi.org/10.62647/ijitce.2025.v13.i2.pp715-725

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